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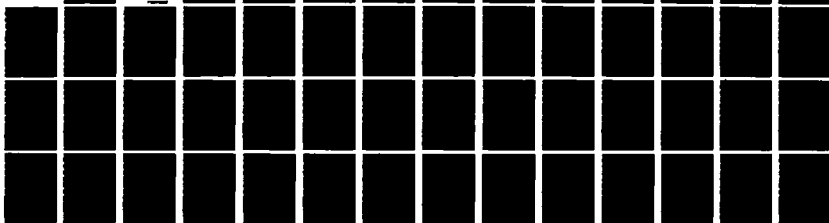
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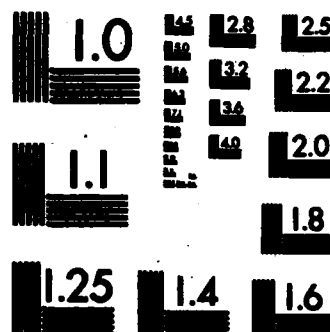
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**RISK, AMBIGUITY, AND INSURANCE**

**Robin M. Hogarth  
University of Chicago  
Graduate School of Business  
Center for Decision Research**

**Howard Kunreuther  
University of Pennsylvania  
The Wharton School  
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**October 1984**

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making by both firms and consumers. After providing examples of the possible effects of ambiguity on the market for insurance, insurance decision making is analyzed theoretically with the aid of the "ambiguity" model developed by Einhorn and Hogarth (1984). The implications of this model are then tested in a series of four experiments using economically sophisticated subjects. The experimental results accord closely with the theoretical predictions, e.g.: firms' minimum selling prices are more sensitive to ambiguity than consumers' maximum buying prices; for firms, the most profitable market segment per dollar coverage occurs for small probability of loss events where consumers are ambiguous but firms are not; conditions exist where people seek rather than avoid ambiguity. Specifically, for high probability events consumers' maximum buying prices are lower under conditions of ambiguity than when such probabilities are known with precision. The experimental results point strongly to the need for more work on the topic using both market-based experiments and empirical field studies.

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## RISK, AMBIGUITY, AND INSURANCE

### 1. Introduction

Insurance has been utilized by economists as a paradigmatic example of a pure contingent claim (Arrow, 1963). In theory it is possible for an individual or firm to purchase protection against the consequences from a given state of nature, paying a premium based on the probability of the loss and the amount of insurance coverage in force.

Expected utility theory is the standard model of choice for determining the optimal amount of insurance to purchase. However, recent controlled laboratory experiments and field survey data suggest that individuals do not behave as though they maximize expected utility when determining whether or not to buy insurance (Arrow, 1982). Prospect theory (Kahneman & Tversky, 1979) has been proposed as an alternative model for describing decision making under risk and explaining some of the insurance anomalies observed in practice.

Both expected utility theory and prospect theory assume that utilities and probabilities are combined independently in determining choices. Furthermore, both theories are axiomatized assuming that probabilities are known precisely. In this paper, we argue that individuals' insurance decisions are partially determined by the precision with which the probabilities of losses can be estimated. More specifically we consider how "ambiguity" regarding probabilities determines the demand for insurance and the premium an individual is willing to pay for a stated amount of coverage. In similar fashion, we investigate the impact of ambiguity on the price an insurer requires to provide protection against a specific loss, and thus how ambiguity influences the performance of insurance markets.

The paper is organized as follows: The next section develops a simple model for investigating equilibrium insurance premiums based on consumers maximizing expected utility and firms maximizing expected profits. Some anomalies in behavior are discussed that appear to be partially related to ambiguities concerning the probabilities of specific outcomes. Section 3 reviews evidence on how ambiguity affects both judgments of probability and choice. We further show how this evidence is consistent with a psychological model of probabilistic judgments made under conditions of ambiguity developed by Einhorn and Hogarth (1984). Section 4 derives the theoretical implications of the Einhorn-Hogarth model for insurance decision making and several predictions are made concerning how consumers and firms react (in terms of prices) to differing degrees of ambiguity. The results of a series of four experiments designed to test these predictions are presented in Section 5. Finally, in Section 6 we present conclusions and suggest areas for further empirical research.

## 2. A simple model of insurance

The following simplified model of consumer and firm behavior is used to investigate the role that ambiguity may play on equilibrium values. Consider a homogeneous group of consumers, each of whom faces a single loss ( $X$ ) that is known precisely. The probability of experiencing this loss, however, is uncertain. Imagine, for example, that several experts disagree on the chance of the particular state of nature occurring. For ease of exposition, assume that each consumer has a prior distribution on this probability which is rectangular with upper and lower bounds given by  $p_{\max}$  and  $p_{\min}$  respectively, and a mean value of  $M(p)$  where

$$M(p) = (1/p^*) \int_{p_{\min}}^{p_{\max}} f(p) dp \quad (1)$$

$$\text{and } p^* = (p_{\max} - p_{\min}) .$$



Insurance firms are willing to offer coverage against the particular loss at a price per dollar coverage ( $r$ ) with the objective of maximizing expected profits ( $E(\Pi)$ ). Thus if each consumer buys  $I$  units of coverage, expected profits for each policy sold is given by:

$$E(\Pi) = [r - M(p)]I \quad (2)$$

It should be clear that the price ( $r$ ) charged should be the same for those firms that have a precise estimate of the probability of a loss given by  $M(p)$  and others that are ambiguous about the probability but where the average estimate is  $M(p)$ . The actual price charged will be a function of each consumer's utility function (which the firm is assumed to know) and the market structure in which the firm operates.<sup>1</sup>

Consumers with net assets of  $A$  will determine the value of  $I$  that maximizes expected utility,  $E[U(I)]$ , where

$$E[U(I)] = \left[ \left( \frac{1}{p} \right)^n \int_{p_{\min}}^{p_{\max}} (f)p \, dp \right] U[A - X + (1-r)I] + \left[ 1 - \left( \frac{1}{p} \right)^n \int_{p_{\min}}^{p_{\max}} f(p) \, dp \right] U[A - rI] \quad (3)$$

For our purposes, note that consumers who maximize expected utility will not be affected by the degree of ambiguity on the probability of a loss if this does not affect  $M(p)$ .

There is nonetheless considerable empirical evidence suggesting that uncertainty about the probability of losses may impact on both consumers' purchase decisions and firms' pricing decisions. For example, even though the price of flight insurance is considerably higher than life insurance, using statistical data on the death rate per passenger trip, substantial demand for this coverage exists. Many factors could contribute to this phenomenon (cf.

Eisner & Strotz, 1961). However, since planes that crash attract disproportionately more publicity than those that do not, it is easy to understand how the chances of a crash loom large in the imaginations of the uninformed public who lack statistical information on accident rates (cf. Tversky & Kahneman, 1974; Combs & Slovic, 1979). More generally, assessing probabilities in ambiguous circumstances necessarily depends on imagination and is thus prone to both the influences of the availability of particular information and the vividness with which recent events have been depicted (cf. Nisbett & Ross, 1980).

A related phenomenon is the lack of interest in flood or earthquake insurance until after a disaster occurs (Kunreuther et al., 1978). People tend to buy this coverage only after experiencing a disaster or learning of others who have suffered severe damage. Since considerable ambiguity exists concerning the chances of these low probability events, there is a tendency for individuals to focus on salient information such as actual losses in making a decision. Prior to the disaster occurring, it appears as if they disregard the event by reasoning that "it can't happen to me" and thus do not buy insurance. After it occurs, however, they change their minds. One is tempted to explain this behavior by a Bayesian argument whereby the probability of an earthquake increases by being updated on the basis of new information. However, the intriguing fact is that over 40 percent of the 1000 respondents in a field survey in earthquake prone areas of California felt that once a severe earthquake occurs, it is less likely to occur in the near future (Kunreuther et al., 1978).

When probabilities are ambiguous, insurance firms are reluctant to market coverage. The case of nuclear power provides a graphic example. Neither risk managers of nuclear utilities nor insurers know enough about the probability

of a nuclear accident. They are thus concerned about a large maximum possible loss even though their estimate of  $M(p)$  associated with such an event is extremely small (U.S. Nuclear Regulatory Commission, 1983). Indeed, the insurance industry has only offered coverage against nuclear risk in connection with federal legislation, the Price Anderson Act. Moreover, given the ambiguity associated with the probability of a catastrophic event, the industry feels that it will be extremely difficult to have companies increase coverage on a voluntary basis to meet the huge losses that could result from an accident (Alliance of American Insurers et al., 1979).

The insurance industry has shown similar attitudes toward providing coverage against political risk. Until recently, few companies offered protection against the potential losses facing industrial firms investing in developing countries with potentially unstable political systems. The principal argument voiced by insurers was that it was difficult to estimate the risk (Kunreuther & Kleindorfer, 1983).

Even with respect to protection such as earthquake insurance where considerable seismological data are available, firms still experience great uncertainty concerning the probabilities of earthquakes. Here the rates set by companies have been higher than past loss experience would justify. Over the sixty-year period since this coverage has been offered in California, \$269 million in total premiums have been collected and only \$9 million in losses have been experienced. In terms of residential insurance in California, the premium to loss ratio over this time period has averaged 30 to 1 (Atkisson & Petak, 1981).<sup>2</sup> These figures imply that even in a relatively competitive environment such as California (where there is limited regulation) there is no interest on the part of firms in lowering their rates.

The above examples of behavior by both individuals and firms suggest that ambiguity or uncertainty concerning probabilities plays an important role in insurance decisions. In addition, the past 30 years have seen a lively discussion in psychology and economics about the relative importance of ambiguity on choice which reinforces these findings. We now present the basic ingredients of this debate and propose a psychological model of how people assess probabilities in ambiguous circumstances based on the work of Einhorn and Hogarth (1984).

### 3. Subjective probabilities, ambiguity, and choice

In 1961, Daniel Ellsberg challenged the notion that subjective probabilities (in the sense of Savage, 1954) could necessarily be inferred from choices among gambles. Ellsberg argued that the ambiguity one experiences in estimates of uncertainty is an important factor in decision making, even though such "second-order" uncertainty should be irrelevant from a normative viewpoint. Moreover, he stated,

Ambiguity is a subjective variable, but it should be possible to identify 'objectively' some situations likely to present high ambiguity, by noting situations where available information is scanty or obviously unreliable or highly conflicting; or where expressed expectations of different individuals differ widely; or where expressed confidence in estimates tends to be low. Thus, as compared with the effects of familiar production decisions or well-known random processes (like coin-flipping or roulette), the results of Research and Development, or the performance of a new President, or the tactics of an unfamiliar opponent are all likely to appear ambiguous (Ellsberg, 1961, pp 660-661).

Since the publication of Ellsberg's paper, several investigators have provided experimental evidence indicating a conservative attitude of "ambiguity avoidance" when people are confronted with prospects of gains (see, e.g., Becker & Brownson, 1964; Gardenfors & Sahlin, 1982, 1983; Yates & Zukowski, 1976). However, since insurance decision making involves potential losses, from our perspective it is more appropriate to investigate the effects

of ambiguity when people face losses. To do so, we first consider how people react to an adaptation of a problem suggested by Ellsberg (as quoted by Becker and Brownson 1964, pp. 63-64, footnote 4).

Consider two urns with 1000 balls in each. In Urn I, each ball is numbered from 1 to 1000 and the probability of drawing any number is .001. In Urn II, there are an unknown number of balls bearing any single number. Thus, there may be 1000 balls with the number 687, no balls with this number, or anything in between. If there is a penalty of \$100 for drawing number 687 from one of the urns, would you prefer to draw from Urn I, Urn II, or be indifferent? For many people, drawing from Urn I (where the probability is known) is the most attractive option. For example, when 58 University of Chicago MBA students answered this problem in a questionnaire administered in a classroom, 45 chose Urn I, 10 were indifferent, and only 3 preferred Urn II. From a theoretical viewpoint, note that attitudes toward risk, as captured in a person's utility function, should play no role in answering this problem since the alternatives all involve the same monetary consequences. The urns differ only concerning the precision of the relevant probabilities.

Einhorn and Hogarth (1984) have recently proposed, and experimentally tested, a psychological model of how people assess probabilities in ambiguous circumstances. This model is based on three principles: (1) In assessing an ambiguous probability, people first anchor on an initial estimate of that probability and then adjust the estimate by the net effect of imagining (i.e., simulating) other values that the probability could take. The initial estimate could be based on past personal experience or data, it might be provided by another party (e.g., an expert), or possibly even generated by considering some analogous situation; (2) the weight given to imagining alternative values of the probability depends on the amount of ambiguity

perceived in the situation--the greater the ambiguity, the greater the weight; and (3) whether people give more, less, or equal weight to imagined values greater or smaller than the initial estimate depends on their attitude toward ambiguity in the circumstances. We elaborate on this below.

Algebraically, the model can be written as

$$S(p) = p + \theta(1 - p - p^{\beta}) \quad (4)$$

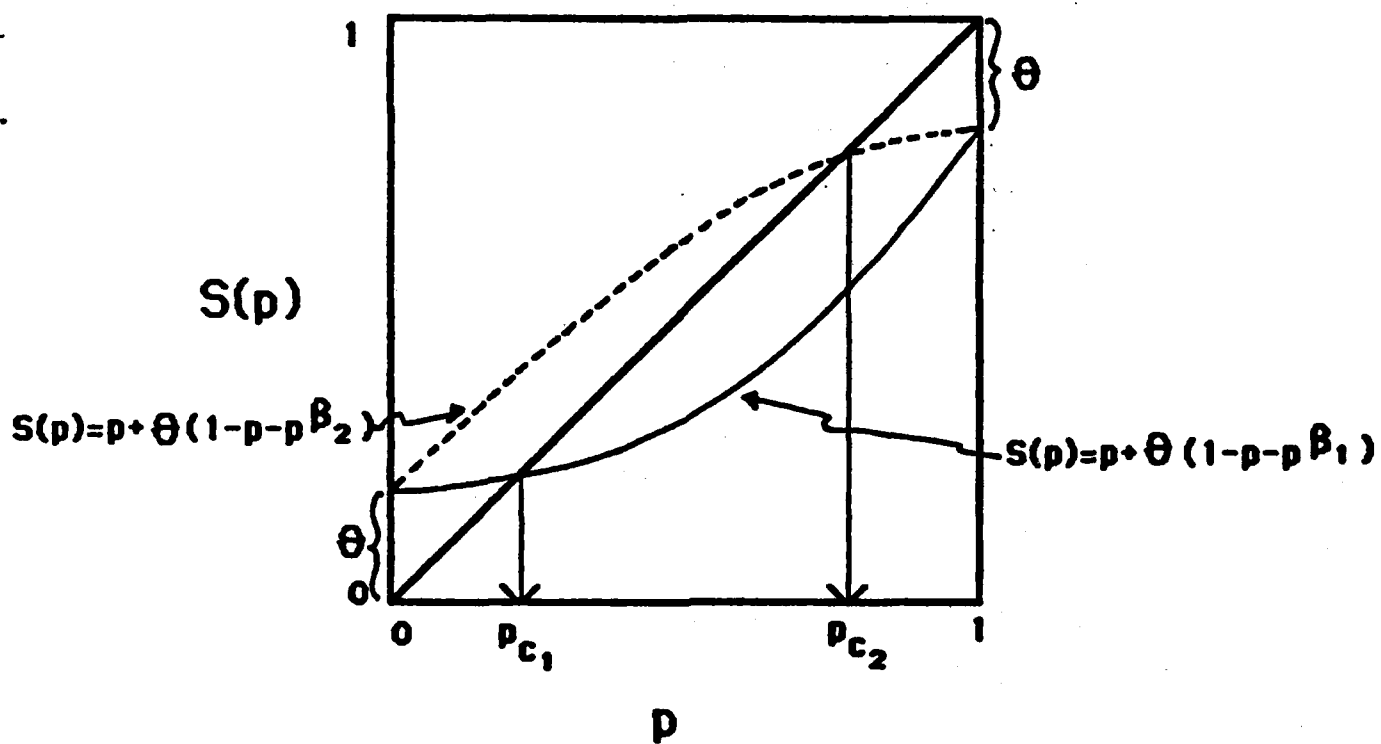
where  $S(p)$  is the reported value of the ambiguous probability;  $p$  is the initial estimate or anchor;  $\theta$  represents perceived ambiguity ( $0 \leq \theta \leq 1$ ); and  $\beta$  reflects the extent to which values of  $p$  above and below the anchor are differentially weighted in imagination, i.e., the person's attitude toward ambiguity in the circumstances ( $\beta \geq 0$ ). In Appendix A, we show how the model is derived algebraically as well as indicating some of its implications. Here we emphasize two points. First, note that  $\theta$  affects the absolute size of the adjustment factor. That is, when  $\theta = 0$ ,  $S(p) = p$ .

Second,  $S(p)$  is regressive with respect to  $p$ . This can be illustrated by considering the effects of different values of  $\beta$  in equation (4). Specifically, in Figure 1 the heavy line illustrates an "ambiguity function"

Insert Figure 1

with  $\beta < 1$  and the dotted line a case where  $\beta > 1$ . ( $\theta$  is shown to be the same in both cases). It is important to note that each value of  $\beta$  defines a unique "cross-over" point,  $p_c$ , where  $S(p) = p$  even when  $\theta \neq 0$ . Thus  $\beta_1$  defines  $p_{c_1}$  such that small probabilities are overweighted and larger probabilities underweighted. That is, when  $\beta < 1$ , more attention is paid to imaginary values of  $p$  that are smaller as opposed to larger than the initial estimate. Thus, over most of the range of  $p$ , the net effect of the adjustment is negative such that  $S(p) < p$ . However, when  $p$  is small (i.e.,  $p <$

**Figure 1**



**Two ambiguity functions**

$p_{01}$ ), the number of imaginary values of  $p$  smaller than the initial estimate is far fewer than those that are greater. Thus, even if smaller values are weighted more heavily than the larger, the net effect of the adjustment is positive such that  $S(p) > p$  for  $p < p_{01}$ . Conversely, when  $s > 1$ , as shown in the dotted curve of Figure 1,  $S(p) > p$  over most of the range of  $p$  since more weight is given to values that are greater rather than smaller than  $p$ . However, when  $p > p_{02}$ ,  $S(p) < p$  since there are far fewer greater as opposed to smaller values of  $p$  that can be imagined. Finally, if  $s = 1$ , the cross-over point (i.e., where  $S(p) = p$ ), is at .5.

To summarize, the Einhorn-Hogarth ambiguity model has two parameters,  $\theta$  and  $s$ .  $\theta$  represents perceived ambiguity and is affected by factors such as meager evidence, unreliable witnesses, lack of causal knowledge of the underlying process generating outcomes, and so on (cf. the quote from Ellsberg reproduced above).  $s$ , on the other hand, denotes attitude toward ambiguity in the circumstances and reflects the extent to which a person pays more attention in imagination to possible values of  $p$  greater or smaller than the initial estimate.

However, what determines  $s$ ? Einhorn and Hogarth (1984) postulate  $s$  to be a function of both individual and situational factors. For the former, one can think of  $s$  as representing a general "pessimism-optimism" measure. Einhorn and Hogarth (1984), for example, found significant correlations in estimates of individuals'  $s$ 's across four inferential tasks. Second, and more importantly, Einhorn and Hogarth (1984) argue that  $s$  is inversely related to the desirability of the outcome that is contingent on the ambiguous probability of concern. The underlying rationale for this statement is that ambiguity induces an attitude of caution rather than riskiness. Thus, when faced, for example, with the desirable possibility of a monetary gain, people



give greater weight in imagination to values of  $p$  below rather than above the anchor (i.e.,  $s < 1$ ). Conversely, when dealing with the undesirable possibility of a loss, this tendency would be reversed.

Finally, we note that when probabilities of events are very small, they could well be ignored in that they fail to have an effect on imagination (see Section 2). Thus, to the extent that the imagined probabilities of events do not surpass some threshold, ambiguity concerning those events will not be an issue. However, note that whereas the Einhorn-Hogarth model does not capture this threshold effect, it does emphasize the importance of the imaginability of events.

#### 4. The ambiguity model applied to insurance decision making

We now consider how the ambiguity model can illuminate insurance decision making. As stated in Section 2, both insurance companies and consumers can experience varying degrees of ambiguity concerning the probabilities relevant to particular contracts. Insurance companies, for example, often have precise knowledge of the probabilities concerning life insurance and automobile theft. On the other hand, there could be considerable vagueness concerning the probabilities relevant to the launching of a satellite from an orbiting space vehicle (cf. Large, 1984).<sup>3</sup> Similarly, a businessman could be vague about the probability of a serious personal accident in a factory, yet estimate precisely the probability of producing defective products with particular equipment.

To simplify the analysis, we consider that insurance companies (firms) and consumers either are, or are not ambiguous about a relevant probability. Crossing these two levels of ambiguity by the two roles (i.e., consumers and firms) leads to the four cases indicated in the table below:

		Consumers	
		Ambiguous	Non-ambiguous
Firms	Ambiguous	a	b
	Non-ambiguous	c	d

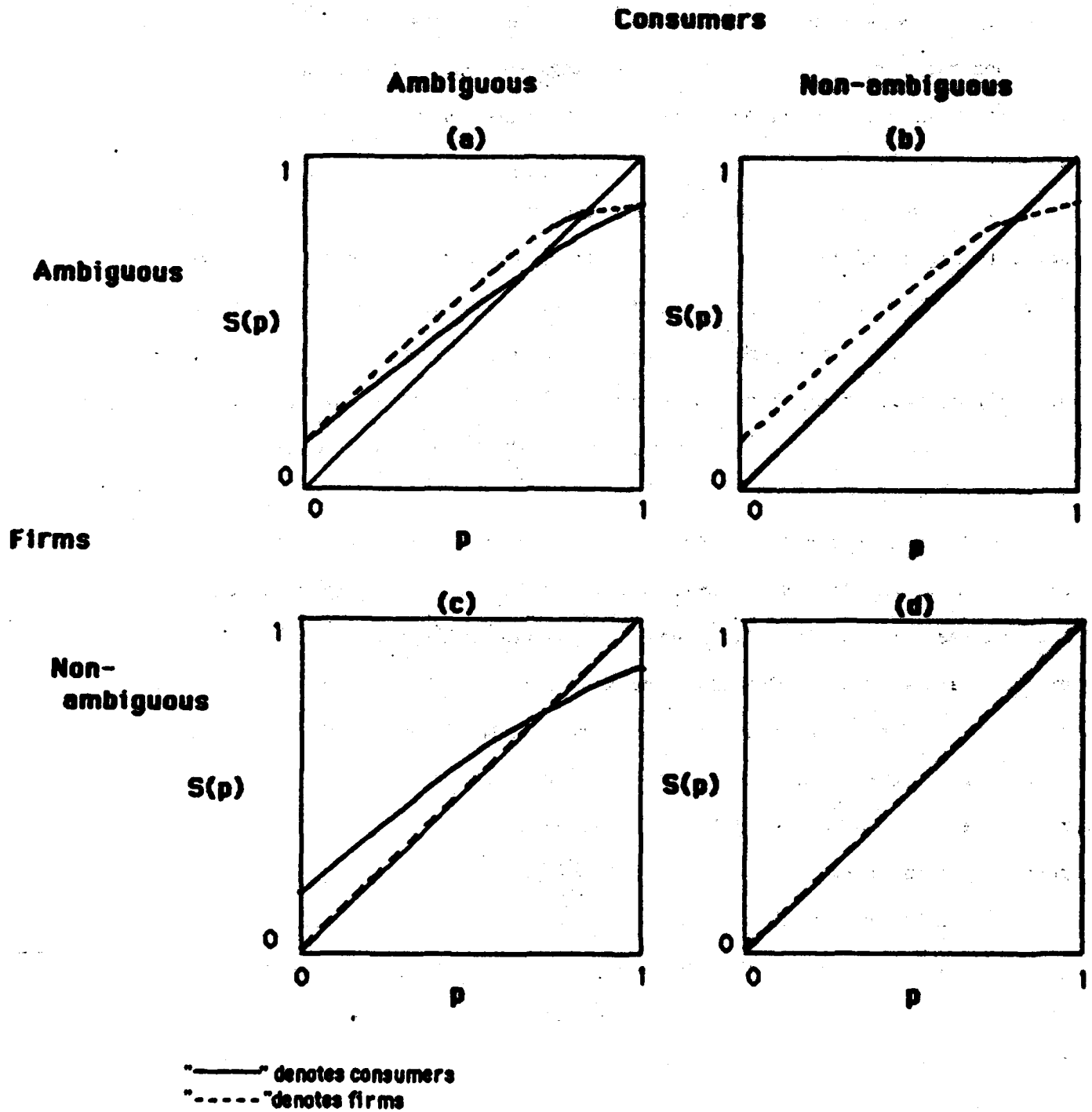
For the purpose of this analysis, we further assume that consumers and firms in the ambiguous conditions experience the same level of ambiguity, i.e.,  $\theta_{\text{consumers}} = \theta_{\text{firms}}$ . On the other hand, we would not expect consumers and firms to have the same  $\beta$  coefficients. Specifically, we assume  $\beta_{\text{firms}} > \beta_{\text{consumers}}$  on the grounds that a person who assumes the risk of a loss has more incentive to pay attention to the possibility that the "true" probability is greater than the initial estimate, than someone who has transferred the risk. Experimental evidence consistent with this transfer effect has been documented by Hershey, Kunreuther, and Schoemaker (1982) and Thaler (1980).

In an insurance context, one would generally expect large values of  $\beta$  since it is the probabilities of potential losses that are of concern. Adding this consideration to the assumption that  $\beta_{\text{firms}} > \beta_{\text{consumers}}$  yields the approximate ambiguity curves of consumers and firms for the four cells of the above matrix as indicated in the four panels of Figure 2.

### Insert Figure 2

Figure 2 assumes that both consumers and firms anchor on the same initial probability estimate prior to adjusting for ambiguity. Furthermore, assume that for a given potential loss, the premium a consumer is prepared to pay is a monotonic (increasing) function of the consumer's  $S(p)$ ; similarly, the premium a firm is prepared to charge is a monotonic (increasing) function of the firm's  $S(p)$ . These assumptions imply the following predictions (refer to

**Figure 2**



**Ambiguity functions:**  
**Consumers and firms for ambiguous and**  
**non-ambiguous cases**

Figure 2):

(a) Consumers and firms are both ambiguous: the firm's price is above the consumer's price across the whole range of  $p$ . This behavior would be consistent with empirical evidence on earthquake insurance and political risk coverage.

(b) The firm is ambiguous, but the consumer isn't: here the firm's price is higher than the consumer's across most of the range of  $p$ . However, note that, in relative terms, the difference between prices decreases as  $p$  increases. Indeed, for high  $p$ , the firm's price drops below the consumer's. Health insurance is the standard example illustrating this case (Arrow, 1963) which may explain why the prices of individual policies are so high relative to standard group plans.

(c) The consumer is ambiguous, but the firm isn't: here the consumer's price exceeds the firm's for small probabilities but the difference decreases and changes sign as  $p$  increases. Automobile insurance would fall in this category since most drivers are less knowledgeable about their chances of an accident than are insurance companies who have detailed records (cf. Svenson, 1981). Note specifically that for low probability events, this case has the most profit potential per dollar coverage for firms in a market that is not perfectly competitive.

(d) Neither consumer nor firm is ambiguous: in this case consumer and firm will have approximately the same prices across the whole range of  $p$ . Insurance offered to airline companies against losses from a crash represents a case where considerable data have been collected by both the airlines and the insurance industry.

In the next section, we describe experimental evidence from laboratory studies undertaken to test the above predictions.

### 5. Experimental evidence

Subjects. We have collected experimental data on the above issues from some 500 individuals. These included MBA students at the University of Chicago and the Wharton School, undergraduates in Decision Sciences at the Wharton School, business executives attending a management course at the University of Chicago, and graduate and undergraduate students at the University of Chicago who volunteered to take part in experiments on decision making. With the exception of the latter group, each of whom was paid \$5 per hour for participating in these and other experiments, data were collected in a classroom setting at the request of the instructor. Subjects were told that there were no "right" answers to the questions and questionnaires were completed in anonymous fashion. In several cases, the classes were later given feedback on group responses which were discussed in light of subsequent course work on decision making.

Since most of these subjects had been exposed to courses in both economics and statistics, they can be described as relatively sophisticated in terms of knowledge relevant to the task. One can, of course, criticize such experimental data on the grounds that respondents' answers had no direct consequences (i.e., subjects were not rewarded for the appropriateness of their answers.) On the other hand, we believe that readers who entertain such criticisms should predict what effects the lack of such consequences would have on results prior to seeing the outcomes of our experiments (cf. Grether & Plott, 1979). One possible prediction is carelessness in response. To guard against this possibility, we sought to replicate our results in various ways.

Stimuli and design. The questionnaires used in all our experiments followed the same general format. We used two scenarios. In one, henceforth referred to as the "defective product" scenario, the owner of a small business

with net assets of \$110,000 seeks to insure against a \$100,000 loss that could result from claims concerning a defective product. Subjects assigned the role of consumers were told to imagine they were the owner of the business. Subjects assigned the role of firms were asked to imagine that they headed a department in a large insurance company and were authorized to set premiums for the level of risk involved.

Ambiguity was manipulated by factors involving how well the manufacturing process was understood, whether the reliabilities of the machines used in the process were known, and the state of manufacturing records. In both ambiguous and non-ambiguous cases a specific probability level was stated (e.g., .01). However, a comment was also added as to whether one could "feel confident" (non-ambiguous case) or "experience considerable uncertainty" (ambiguous case) concerning the estimate. Uniformity of perceptions of ambiguity was controlled by describing the situations by the same words in both the consumer and firm versions.

The second scenario, henceforth known as the "Brown River" scenario, also involved a small businessman, a loss of \$100,000 and a large insurance company. In this case, the potential loss was contingent on the flooding of a warehouse "located on the Pennndiana floodplain." In the non-ambiguous version subjects were told that the probability of a flood destroying the inventory in the warehouse could be confidently estimated by experts on the basis of considerable hydrological data. In the ambiguous case, subjects were told that limited data existed concerning the flooding of the Brown River. Moreover, hydrologists were "sufficiently uncertain about this event so that this annual probability could range anywhere from zero to 1 in 50 (i.e., .02) depending on climatic conditions." (Copies of the experimental stimuli may be obtained by writing to the authors.)

Our experiments tested effects in both between- and within-subjects designs and we also used two response modes. In the first mode, consumers were asked to state maximum buying prices and firms indicated minimum selling prices for insurance. In the second mode, both consumers and firms were given two levels of prices and asked whether they would trade at those prices. We now present the results of our four experiments.

Experiment 1. We first consider data collected from 112 University of Chicago MBA students. This study involved the defective product scenario with a potential loss of \$100,000. Each subject was assigned the role of a consumer or a firm and responded to both the ambiguous and non-ambiguous versions of the scenario at one probability level. Four probability levels were investigated ( $p = .01, .35, .65, \text{ and } .90$ ). The design of this experiment therefore involved 3 factors, 2 of which were between subjects (i.e., role of consumer or firm, and probability level) and 1 within subjects (i.e., ambiguous vs. non-ambiguous scenarios).

Results of the experiment are first presented in Table 1 in terms of

Insert Table 1 and Figure 3 here

median prices of firms and consumers for all experimental conditions. The trends in that table are further illustrated by Figure 3 which shows median prices as a function of probability levels for firms and consumers in the ambiguous conditions.

It is instructive to compare Figure 3 with panel (a) in Figure 2. Note that the median prices of firms (under ambiguity) exceed those of consumers at all four probability levels. Moreover, for  $p = .65$  and  $p = .90$ , median consumer prices are substantially below expected value. In the non-ambiguous case, however, the median prices of both firms and consumers are close to expected value for all probability levels and are not explicitly shown in

TABLE 1

## Experiment 1: Median Prices of Firms and Consumers

Defective product scenario Loss = \$100,000		Median prices (\$)					
		Firms <sup>1</sup>		Consumers <sup>1</sup>		Differences between median prices (\$) of firms and consumers <sup>2</sup>	
		Ambiguous	Non-ambiguous	Ambiguous	Non-ambiguous		
.01	(15)	2,500 **	1,000	1,500 *	1,000	1,000 ns	0 ns
.35	(14)	52,500 **	37,500	35,000 ns	35,000	17,500 **	2,500 ns
.65	(13)	70,000 ns	65,000	45,000 **	65,000	25,000 ***	0 **
.90	(14)	90,000 ns	90,000	60,000 **	82,500	30,000 **	7,500 **

Two-tailed tests used throughout:

<sup>1</sup>Wilcoxon test.<sup>2</sup>Mann-Whitney test.

\* p &lt; .05

\*\* p &lt; .01

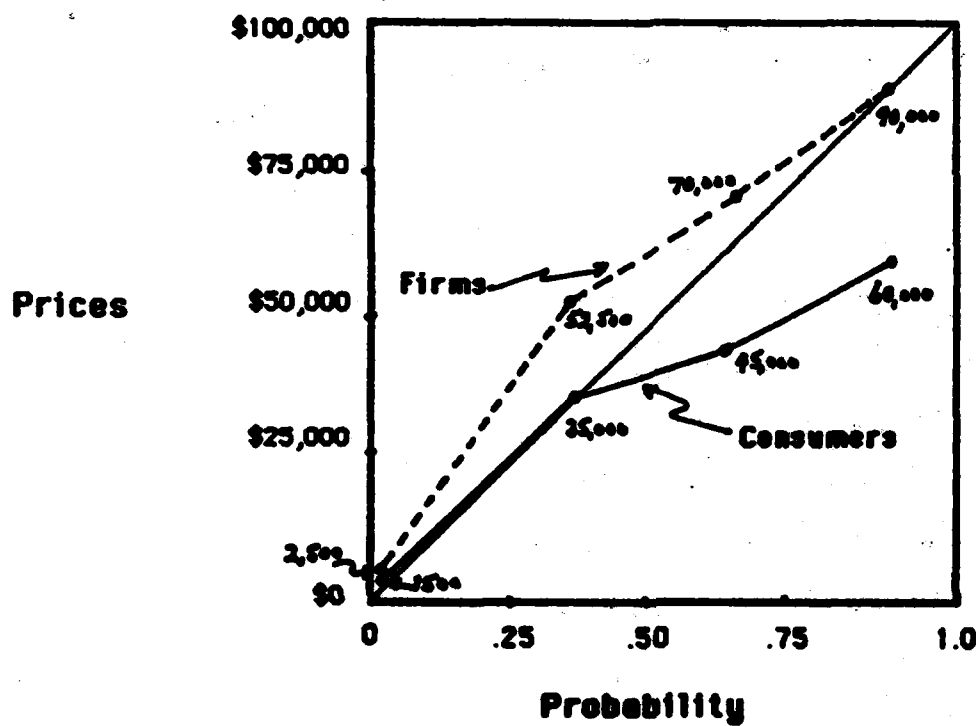
\*\*\* p &lt; .001

ns not significant

(n) number of subjects in experimental condition



**Figure 3**



**Experiment 1-- Median selling prices  
for ambiguous consumers and firms**

**Note:** Median prices for the non-ambiguous case are not shown  
since these all fell close to the diagonal.

Figure 3. Consumers can therefore be said to exhibit ambiguity preference in their stated prices at the two higher probability levels.

Visual analysis is supported by statistical tests (Wilcoxon or Mann-Whitney) of the differences between distributions that are detailed in Table 1: (1) prices of firms exceed those of consumers when both are ambiguous except when  $p = .01$  (although the difference here is in the predicted direction i.e., 2,500 vs. 1,500); (2) prices of firms in the ambiguous condition exceed those in the non-ambiguous conditions for  $p = .01$  and  $p = .35$ , and are not significantly different from non-ambiguous prices at  $p = .65$  and  $p = .90$ ; (3) differences between prices of consumers in the ambiguous and non-ambiguous conditions are positive at  $p = .01$ , and negative at  $p = .65$  and  $p = .90$ . There is, however, no difference at  $p = .35$ . In short, the pattern of results exhibited in Table 1 and Figure 3 corresponds closely to the predictions of the ambiguity model.

Table 2 provides an analysis of what would have happened had individual

Insert Table 2 here

firms and consumers traded at their stated prices. We present three kinds of statistics for the different types of situations represented by the four panels of Figure 2. These are: (1) the proportion of trades that would have taken place had firms and consumers been matched on a one-to-one basis. This was done by separately rank-ordering firms and consumers by stated prices (high to low). Next, matches were found for consumers on a one-to-one basis starting first with the consumer prepared to pay the highest price and then moving down the list. This process continued until the only consumers left were those whose prices were all below those of the lowest price offered by the remaining sellers; (2) the proportion of possible trades that would have occurred had all consumers been able to buy at firms' median prices; and (3) a

TABLE 2

## Experiment 1 - Firms and Consumers: Trades at Stated Prices

	Probability Levels	(a)		(b)		(c)		(d)	
		Firm: A	Consumer: A	Firm: A	Consumer: NA	Firm: NA	Consumer: A	Firm: NA	Consumer: NA
1. Proportion of possible trades on a one-to-one basis	.01:	.67		.62		.93		.92	
	.35:	.43		.43		.64		.64	
	.65:	.46		.46		.46		.69	
	.90:	.43		.71		.36		.57	
2. Proportion of possible trades using firms' median prices	.01:	.20		.08		1.00		.92	
	.35:	.00		.00		.13		.20	
	.65:	.00		.00		.36		.57	
	.90:	.21		.43		.21		.43	
3. Average "producer surplus" per trade divided by expected value	.01:	.34		.11		1.20		.31	
	.35:	.18		.19		.24		.25	
	.65:	.04		.08		.00		.02	
	.90:	.30		.15		.12		.09	

A: Ambiguous condition.

NA: Non-ambiguous condition

normalized measure of average "producer surplus" per trade in each condition when consumers and firms were matched on a one-to-one basis. This figure was calculated by taking the average surplus (i.e., consumer's price less firm's price) per trade consummated in a given condition, and then dividing this quantity by the expected value of the premium appropriate to that condition. This normalization by expected value was used to facilitate comparisons between different probability levels.

Table 2 indicates several systematic trends, both across probability levels and within ambiguous/non-ambiguous conditions. Moreover, these trends are consistent across all measures. First, more trades take place when probabilities are small. The exception is column (b) where ambiguous firms are paired with non-ambiguous consumers. Here more trades take place when the probability is high. However, note that this is consistent with the ambiguity model, since in this case firms' stated probabilities exceed those of consumers except at high values--see Figure 2(b). Second, more trades generally take place when firms are not ambiguous. This is also consistent with Figure 2--note, in particular, panels (c) and (d). Third, the normalized measure of average producer surplus per trade is largest for  $p = .01$  when consumers are ambiguous, but firms are not. Moreover, note from Figure 2(c) that this situation corresponds to the largest positive difference that arises when the firm's  $S(p)$  is subtracted from that of the consumer. In fact, we suspect that a large proportion of all real-world insurance offered by firms takes place precisely in this potentially most profitable segment. However, more empirical data are needed to confirm this conjecture.

Experiment 2. The second experiment also involved the defective product scenario. This time both ambiguity and role were between subject factors. That is, subjects were assigned at random to one of four conditions (2 ambigu-

ity  $\times$  2 roles). However, both probabilities and the size of the loss were treated as within-subject factors. Specifically, each subject in a given condition responded to 16 stimuli constructed from crossing 4 probability levels (.01, .35, .65, .90) by 4 levels of loss (\$1000, \$10,000, \$50,000, \$100,000).

In this experiment, subjects were graduate and undergraduate students recruited at the University of Chicago to participate in experiments on decision making and remunerated at a rate of \$5 per hour. Thus the questions they answered were presented to them along with a series of questions from other experiments. Subjects first received one of the 16 stimuli and responded to it before turning a page in a booklet to discover that they would have to respond to more stimuli (probability  $\times$  size of loss combinations) while imagining themselves to be in circumstances otherwise identical to those described in the first stimulus.

An earlier pilot study with this population of subjects revealed much ignorance about insurance as well as confusion concerning the experimental task. At the end of this task, therefore, subjects were asked, on a separate sheet of paper, whether they had ever purchased insurance. Of the 85 subjects who participated, 39 indicated having purchased insurance. It was their responses that are retained in the analysis. Whereas this criterion involved eliminating many possibly valid responses, it also provided an objective criterion for eliminating a subset of responses that showed extreme variability.

Table 3 reports the median responses of the 39 subjects. In addition,

Insert Table 3 here

the expected values of the losses in each condition are shown in the right hand column to facilitate comparisons.

Results of testing differences between the distributions of prices of

TABLE 3

Defective product scenario: Median firm and consumer prices  
across different levels of losses and probabilities

Losses	Probabilities	M e d i a n s (\$)						Expected Value
		F i r m s		C o n s u m e r s				
		Ambiguous	Non-Ambiguous	Ambiguous	Non-Ambiguous	Ambiguous	Non-Ambiguous	
<u>\$1,000</u>	.01	50	*	10	ns	10	10	10
	.35	500	*	350	ns	350	350	350
	.65	825	*	650	ns	625	650	650
	.90	950	*	900	ns	825	900	1,000
<u>\$10,000</u>	.01	500	*	100	ns	100	100	100
	.35	5,000	ns	3,500	ns	3,500	3,500	3,500
	.65	8,250	*	6,500	ns	6,250	6,499	6,500
	.90	9,500	*	9,000	ns	8,250	9,000	9,000
<u>\$50,000</u>	.01	2,500	**	500	ns	500	500	500
	.35	25,000	ns	17,500	ns	17,000	17,500	17,500
	.65	40,000	*	32,500	ns	27,500	32,500	32,500
	.90	47,500	*	45,000	ns	40,000	44,900	45,000
<u>\$100,000</u>	.01	5,000	*	1,100	*	2,000	1,000	1,000
	.35	50,000	ns	35,000	ns	35,000	35,000	35,000
	.65	75,000	*	65,000	ns	55,000	65,000	65,000
	.90	95,000	*	90,000	ns	82,500	90,000	90,000
(n =		9	9	8	8	13)		

Mann-Whitney test: \*  $p < .05$

\*\*  $p < .01$

ns not significant

n indicates number of subjects in each condition

both firms and consumers in the ambiguous and non-ambiguous cases are also shown. Since sample sizes are small, individual significance levels are less important than the overall pattern of results for both firms and consumers. This clearly replicates the results of experiment 1. The statistical tests also show significant ambiguity effects for firms. In addition, there is one important effect for consumers, namely when  $p = .01$  for the potential \$100,000 loss, the median price is twice as high in the ambiguous as opposed to the non-ambiguous case.

Experiment 3. In experiment 3 a series of tests were carried out with different groups of subjects using both the defective product and Brown River scenarios. The medians of firm and consumer prices for different values of  $p$  are presented in Tables 4a and 4b. The experiment can be thought of as involving three categories of tests: (1) A within-subjects test of ambiguous vs. non-ambiguous stimuli for subjects assigned the roles of either firms or consumers. Here each subject responded as either firm or consumer to both the

Insert Tables 4a and 4b here

ambiguous and non-ambiguous versions of the stimuli. These tests involved the defective product scenario at various probability levels using different populations of subjects; (2) Tests using between-subject comparisons of the effects of the ambiguity variable. In this design subjects saw either only the ambiguous or non-ambiguous versions of the stimuli for the defective product scenario; (3) Tests of an analogous between-subject ambiguity manipulation involving the Brown River scenario. Results of the first two categories of tests are presented in Table 4a and the third in Table 4b.

The pattern of results is consistent both with the predictions of the ambiguity model and the results of experiments 1 and 2. Wilcoxon and Mann-Whitney tests (as appropriate) of the differences between distributions

TABLE 4a

Additional buying and selling prices for defective product scenario

Defective product scenario:

Loss = \$100,000

	M e d i a n s				
	F i r m s		C o n s u m e r s		
	Ambiguous	Non-ambiguous	Ambiguous	Non-ambiguous	Expected Value
1. Within-subjects design					
Probability = .01					
University of Chicago students	-	-	4,000 (19)	** 1,050 (20)	1,000
Executives	10,000 (16)	** 1,000 (16)	5,000 (16)	** 1,000 (16)	1,000
Probability = .40					
University of Chicago students	48,000 (14)	* 42,000 (15)	25,000 (17)	ns 36,000 (17)	40,000
Executives	50,000 (18)	ns 57,500 (18)	30,000 (15)	ns 50,000 (15)	65,000
2. Between-subjects design					
Probability = .01					
Wharton undergraduates	2,000 (39)	* 1,000 (41)	5,000 (42)	*** 1,000 (40)	1,000
Probability = .90					
Wharton undergraduates	90,000 (38)	* 90,000 (40)	50,000 (39)	ns 90,000 (39)	90,000

Wilcoxon and Mann-Whitney tests as appropriate

\*  $p < .05$ \*\*  $p < .01$ 

ns not significant

The number of subjects in each condition is indicated in parentheses.



TABLE 4b

Buying and selling prices for Brown River scenario

Loss = \$100,000

	M e d i a n s					
	F i r m s			C o n s u m e r s		
	<u>Ambiguous</u>	<u>Non-ambiguous</u>	<u>Ambiguous</u>	<u>Ambiguous</u>	<u>Non-ambiguous</u>	<u>Non-ambiguous</u>
3. <u>Between-subjects design</u>						
Probability = .01						
University of Chicago students	2,000 (29)	ns	1,030 (26)	2,000 (25)	ns	1,400 (30)
Wharton undergraduates	2,000 (41)	***	1,000 (41)	2,000 (40)	***	1,000 (41)

Mann-Whitney tests

\* p &lt; .05

\*\* p &lt; .01

\*\*\* p &lt; .001

ns not significant

The number of subjects in each condition is indicated in parentheses.

indicate that, at the lowest probability level ( $p = .01$ ), the results are all statistically significant with but one exception, the data for University of Chicago students using the Brown River scenario (Table 4b). However, these subjects comprised the most heterogeneous group tested and some of their responses showed great variability. Unfortunately we did not collect supplementary data on this group (as in experiment 2) that would have permitted us to eliminate subjects who did not fully understand the context of the scenarios. A more surprising finding is that the large differences between consumers' medians at the higher probability levels ( $p = .65$  for executives and  $p = .90$  for Wharton undergraduates, Table 4a) did not result from distributions judged by formal tests to be significantly different. Note, however, that the medians do indicate the ambiguity preference implied by the model.

Experiment 4. In experiments 1-3, subjects were required to state maximum buying prices or minimum selling prices at which they were willing to trade. What would happen if consumers and firms were asked if they would be prepared to trade at a pre-specified price?

The effects of this response mode were tested using both the defective product and Brown River scenarios. For both scenarios, the loss was \$100,000. Three sets of stimuli were generated by varying probabilities at the .01 and .65 levels for the defective product scenario, and the .01 level for the Brown River scenario. Each subject was allocated at random to one of four conditions created by crossing the 2 roles  $\times$  2 levels of ambiguity. This resulted in a between-subjects design for each of the 3 sets of stimuli involved. For the defective product scenario, however, subjects in the ambiguous condition at the .01 probability level were also allocated to the non-ambiguous condition at the .65 level, and subjects in the non-ambiguous

condition at the lower probability level responded to the ambiguous stimulus at the higher level.

Each subject was either a consumer or firm for the entire experiment. Those responding to the defective product scenario were all University of Chicago MBA's; subjects responding to the Brown River scenario included both University of Chicago and Wharton MBA's as well as executives attending a University of Chicago management program. Since the results from the different sub-groups responding to the Brown River scenario do not differ significantly, they have been aggregated for the purpose of this analysis.

Scenarios were identical to those used in the other studies except that subjects were required to respond by stating whether they would trade ("Yes" or "No") at a given price. Having answered this question, subjects turned a page in their experimental booklets and were asked the same question with respect to a different price. To simulate trading conditions, the second price for consumers was lower than the first, whereas the reverse order was used for firms (i.e., lower prices were stated first). Our previous experiments indicated that the defective product scenario induced more ambiguity than the Brown River scenario. We attempted to allow for this difference at the .01 probability level by setting the prices for the former at \$1,500 and \$3,000, and at \$1,100 and \$2,500 for the latter (expected value = \$1,000). The prices for the .65 probability level for the defective product scenario were set at \$45,000 and \$67,500 (expected value = \$65,000).

The results of experiment 4 are presented in Table 5 in the form of

Insert Table 5 here

percentages of subjects prepared to trade in the different conditions. Consider first the results for consumers in both scenarios at the .01 probability level. For the defective product scenario, there is a marked

TABLE 5

Percentages of subjects prepared to trade at given prices -- Experiment 4

		Defective product scenario (Loss = \$100,000)			Brown River scenario (Loss = \$100,000)		
		Probability = .01			Probability = .01		
		\$1,500	\$3,000	n*	\$1,100	\$2,500	n†
		(%)	(%)		(%)	(%)	
Consumers:	Ambiguous	87	83	23	88	47	43
	Non-ambiguous	77	50	22	78	48	50
Firms:	Ambiguous	16	36	25	36	89	45
	Non-ambiguous	67	87	15	73	90	48

		Probability = .65		
		\$45,000	\$67,500	n*
		(%)	(%)	
Consumers:	Ambiguous	50	9	22
	Non-ambiguous	78	9	23
Firms:	Ambiguous	27	40	15
	Non-ambiguous	8	64	25

\*Subjects were MBA students at the University of Chicago (n = number of subjects).

†Subjects were MBA students at the University of Chicago and Wharton as well as executives attending a University of Chicago management program (n = number of subjects).

effect for ambiguity at the \$3,000 price level: 83% of ambiguous consumers would trade at that price as against 50% of non-ambiguous consumers ( $\chi^2_1 = 6.42$ ,  $p = .01$ ). On the other hand, there is no ambiguity effect in the Brown River scenario. That is the percentages of consumers prepared to trade at both price levels are not significantly different.

For firms, there are distinct ambiguity effects at the  $p = .01$  level in both scenarios. In the defective product scenario, far fewer firms are prepared to trade in the ambiguous as opposed to non-ambiguous condition. At \$1,500 the figures are 16% vs. 67% ( $\chi^2_1 = 9.06$ ,  $p < .01$ ), and at \$3,000 one observes 36% vs. 87% ( $\chi^2_1 = 10.76$ ,  $p = .001$ ). In the Brown River scenario, there is no ambiguity effect at the higher price (\$2,500: 89% vs. 90%) but at \$1,100 the 36% vs. 73% result is statistically significant ( $\chi^2_1 = 14.09$ ,  $p < .001$ ).

Now consider the consumers at the .65 probability level in the defective product scenario. Data from experiments 1-3 suggest that at this probability level consumers' median prices are less than the expected value (\$65,000) in the ambiguous condition, and at most \$65,000 in the non-ambiguous condition. It is therefore no surprise that there is little demand at \$67,500 in either condition (both at 9%). On the other hand, the greater demand for insurance at \$45,000 in the non-ambiguous condition, i.e., 78% vs. 50%, is consistent with our earlier findings of ambiguity seeking at high probability levels. The statistical significance of this result, however, is weaker than our other conclusions ( $\chi^2_1 = 3.49$ ,  $.05 < p < .10$ ).

For firms, our previous results show little difference between the ambiguous and non-ambiguous conditions at the .65 probability level and this result holds up again. Specifically, there is no significant difference at \$67,500 ( $\chi^2_1 = 1.72$ ) although there is a tendency for ambiguity seeking at

\$45,000, i.e., 27% vs. 8% ( $\chi^2_1 = 3.50$ ,  $.05 < p < .10$ ). Finally, an interesting comparison can be made for firms across the .65 and .01 probability levels. Specifically, in the ambiguous condition approximately the same proportion of firms will trade at \$3,000 when  $p = .01$  as at \$67,500 when  $p = .65$  (i.e., 36% and 40%). However, whereas the former price is 3 times greater than the expected value, the corresponding ratio is only 1.04 in the latter case. It should be noted that the relative sizes of these ratios are entirely consistent with the implications of the ambiguity curves drawn in Figure 2. Analogous remarks can also be made when comparing consumers across the two probability conditions.

To summarize, the results of experiment 4 essentially replicate the results of experiments 1-3 using a different form of response mode (preparedness to trade at specific prices vs. stating minimum selling/maximum buying prices). The one exception concerns the lack of an ambiguity effect for consumers in the Brown River scenario with  $p = .01$ . A possible reason is that the \$2,500 price was too high relative to the ambiguous description used in that scenario. Indeed, this speculation is supported by the fact that there was also no ambiguity effect for firms at this price. On the other hand, that firms should be more sensitive to ambiguity at the lower price (\$1,100) is consistent with the model as are the analogous data concerning the defective product scenario.

## 6. Conclusions

The results of the above experiments suggest that ambiguity influences decisions by both firms and consumers with respect to insurance. In particular, when information is ambiguous firms will want to charge premiums for low probability events that are well in excess of expected value. This behavior is consistent with casual evidence on real-world insurance markets

and closely follows predictions from the Einhorn-Hogarth model of ambiguity.

These preliminary findings suggest a number of areas for future empirical research. On the consumer side, in addition to further investigating the role of ambiguity on price, it would be of interest to examine how ambiguity affects the types of insurance coverage that consumers are prepared to purchase. For example, the demand for low deductibles in both automobile (Pashigian et al., 1966) and health insurance (Fuchs, 1976) has been particularly puzzling to economists since the premium to loss ratio for these types of coverage is extremely high. However, if consumers estimate the probability of an accident as low, but are ambiguous about such estimates, it follows from the ambiguity model that they will be willing to purchase this type of protection at prices considerably in excess of actuarial value. Similar reasoning can be applied to protection that is bought against rare but life threatening events. For example, it would be interesting to determine demand for insurance against various forms of cancer or AIDS, diseases which are highly salient but where there is considerable ambiguity concerning the chances of an individual contracting the disease.

In terms of marketing insurance for events that are inherently ambiguous, the model also has some specific implications. For example, since the model implies that consumers are prepared to pay more per dollar of coverage as probabilities decrease, this suggests marketing strategies where contracts are framed so that probabilities are small. This can be achieved in two ways: (a) reducing the period for which coverage is provided, e.g., from a year to six months; or (b) writing separate contracts for specific risks as opposed to providing more comprehensive policies (cf. Schoemaker & Kunreuther, 1979). In following such prescriptions, however, marketers should take care that probabilities of losses do not become so small that they fall below consumers'

thresholds of awareness (cf. Slovic et al., 1978).

The manner in which past experience affects demand for insurance is another area for future research. We have hypothesized that people who have substantial experience with certain low probability events have little ambiguity and hence are less likely to purchase insurance or protection against such events. Thus with respect to flight insurance, this implies that frequent travellers, such as businessmen, are much less likely to purchase coverage than those who fly on an occasional basis. Similarly, we would predict that credit card customers who receive "free" flight insurance when paying for air travel with their credit cards will value this service more to the extent that they lack experience of flying. Lack of experience regarding certain events may also explain the dread associated with accidents from technological facilities such as nuclear power plants (Slovic et al., 1983). More generally, people may consider events that can only occur once in a lifetime, such as death or a serious illness, as inherently more ambiguous for them personally than events that are repeatable (e.g., a household fire or theft). Firms, on the other hand, have the advantage of treating individual ambiguities as precise statistics at the aggregate level.

As discussed earlier, providing nuclear coverage is a concern of the insurance industry. Officially, all property liability insurance policies issued in the United States exclude claims for damage to one's dwelling, automobile, boat, and other property by radiation and contamination from a nuclear facility. The insurance industry is opposed to providing this kind of coverage, claiming that the risk is not insurable because of the ambiguity associated with potential losses (U.S. Nuclear Regulatory Commission, 1983). It would be interesting to determine what price the industry would be willing to charge for a certain amount of coverage and what the demand for this



insurance would be. We hypothesize that there would be considerable demand by consumers even with premiums substantially higher than actuarial values because of the great ambiguity associated with the event. However, given the firms' own ambiguities, it is an open question as to whether the premiums they would be prepared to charge would be considered reasonable by consumers.

Turning now to controlled laboratory experiments, we are interested in extending the results of this study to a market-based situation in the spirit of Plott (1982) and Smith (1982) where buyers and sellers can interact with each other to determine insurance premiums using real monetary stakes. Thus, an experimental design similar to the  $2 \times 2$  matrix used in this study can be used to investigate the impact of ambiguity on equilibrium prices in a market setting. Pilot experiments undertaken by Camerer and Kunreuther (1984) suggest that, for low probability events involving ambiguity, insurers demand considerably higher premiums than consumers are prepared to pay--a result consistent with those reported here.

Since warranties and service contracts are forms of insurance, one can also investigate these phenomena within the present framework. For example, the warranty experiments of Palfrey and Romer (1984) could be extended to cases in which agents are ambiguous about the probability of a failure. Similarly, experiments could investigate the market for service contracts by varying the probabilities of requiring service, costs, and ambiguity. According to the Einhorn-Hogarth model, consumers should express less interest in purchasing a warranty or service contract when the probabilities of breakdowns or losses are both high and ambiguous, as opposed to non-ambiguous situations where they are known to be high. Thus, reasoning in analogous manner to our earlier comments on comprehensive insurance, the model predicts greater demand under ambiguity for a series of lower probability of loss con-

tracts than for an equivalent comprehensive contract where the probability of requiring at least one of the services is high.

Finally, we recognize that in naturally occurring situations the effects of ambiguity cannot be easily separated from other aspects affecting choice under uncertainty. The magnitude and nature of the loss, the salience or vividness of the events, feelings of regret (Bell, 1982; in press) and even the manner in which people become aware of and "frame" their decisions (cf. Tversky & Kahneman, 1981), can all impact significantly on choice. Nonetheless, we are impressed by the wide variety of economic phenomena where ambiguity does seem to play a significant role and believe that this topic should receive greater attention than it has to date.

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## APPENDIX A

## Model for Assessing Probabilities under Ambiguity

The model is discussed in Einhorn and Hogarth (1984) in some detail. It can be derived algebraically as follows: First, denote the stated, ambiguous probability as  $S(p)$  where

$$S(p) = p + k \quad (A.1)$$

That is,  $S(p)$  is obtained by anchoring on the initial estimate,  $p$ , and then adjusting for the net effect of imagining alternative values of  $p$  greater and smaller than the initial estimate. This net adjustment is represented by  $k$ , which can also be written as

$$k = k_g - k_s \quad (A.2)$$

where  $k_g$  denotes the effect of imagining values of  $p$  greater than the initial estimate, and  $k_s$  the effect of imagining smaller values. Note that both  $k_g$  and  $k_s$  must be affected by the value of the initial estimate,  $p$ , since there can be no simulation below  $p$  when  $p = 0$ , and none above when  $p = 1$ . Moreover, the maximum upward adjustment is  $(1-p)$  and the maximum downward adjustment is  $p$ . Let  $\theta$  ( $0 \leq \theta \leq 1$ ) represent perceived ambiguity such that maximum adjustments would occur under complete ambiguity ( $\theta = 1$ ), and zero adjustments under no ambiguity ( $\theta = 0$ ). This suggests that the effects of simulating values greater and smaller than the anchor,  $p$ , can be represented as proportions of the maximum adjustments where  $\theta$  is the constant of proportionality, i.e.,

$$k_g = \theta(1-p) \quad (A.3a)$$

$$\text{and } k_s = \theta p \quad (A.3b)$$

However, note that equation (A.3) does not allow for the possibility that

differential attention might be given to imagining values of  $p$ , that are larger as opposed to smaller than the initial estimate. This is modeled by redefining  $k_p$  by  $ep^s$  where  $s \geq 0$  represents the person's attitude toward ambiguity in the circumstances. (Einhorn & Hogarth, 1984, also consider alternative forms of differential weighting.) To aid understanding, note that if  $s = 1$ , equal attention is given in imagination to values of  $p$  greater and smaller than the initial estimate; for  $s < 1$ , more weight is given to smaller values; and if  $s > 1$ , more weight is given to larger values.

Given the above, equation (A.2) can be re-written as

$$\begin{aligned} k &= e(1-p) - ep^s \\ &= e(1-p-p^s) \end{aligned} \quad (A.4)$$

such that equation (A.1) becomes

$$S(p) = p + e(1-p-p^s) \quad (A.5)$$

which is equation (4) in the text.

An important implication of equation (A.5) is that it can imply non-additivity of the probability judgments of complementary events. Specifically, consider the sum of  $S(p)$  and  $S(1-p)$ . This is,

$$\begin{aligned} S(p) + S(1-p) &= p + e(1-p-p^s) + (1-p) + e[1-(1-p) - (1-p)^s] \\ &= 1 + e[1-p^s - (1-p)^s] \end{aligned} \quad (A.6)$$

Equation (A.6) specifies conditions for additivity and non-additivity: (i) additivity of the probabilities of complementary events obtains if  $e = 0$ , or  $s = 1$ , or  $p = 0$ , or  $p = 1$ ; otherwise there is non-additivity, specifically: (ii) sub-additivity if  $s < 1$ ; and (iii) super-additivity if  $s > 1$ . Einhorn and Hogarth (1984) have demonstrated non-additivity experimentally in accordance with equations (A.5) and (A.6) in tasks involving both judgments of likelihood and choices between gambles.



## Footnotes

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<sup>1</sup>At one extreme of market structure, if a firm is in a purely competitive environment then  $r = M(p)$  since  $E(\pi) = 0$  for each firm. At the other extreme, a monopolistic firm will set a premium based on the consumer's demand for insurance as a function of  $r$ .

<sup>2</sup>The only year during the sixty-year period when losses exceeded premium payments was 1933 when paid claims amounted to \$1.1 million and premiums were \$.95 million.

<sup>3</sup>In a Wall Street Journal article (June 21, 1984) on the space insurance industry, the effects of ambiguity on premiums charged by firms are clearly recognized. For example, consider the following quote from James Barrett, president of the Washington-based International Technology Underwriters:

"... if you're asking me to risk the capital of my company, then I've got to be comfortable that you're going to succeed. If we're not comfortable, we're not going to insure it, or we'll charge you like hell for it" (Large, 1984).

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